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Nonlinear Model Predictive Speed Control of Electric Vehicles Represented by Linear Parameter Varying Models with Bias terms

Navid Vafamand, Mohammad Mehdi Arefi*, *Senior Member, IEEE*, Mohammad Hassan Khooban, *Senior Member, IEEE*, Tomislav Dragičević, *Senior Member, IEEE,* and Frede Blaabjerg, *Fellow, IEEE*

***Abstract*— This paper investigates a novel approach to design a nonlinear optimal model predictive controller for the speed control of constrained nonlinear electric vehicles (EVs). The proposed approach employs a linear parameter varying (LPV) model including bias terms and a model predictive scheme. The controller design conditions are derived in terms of linear matrix inequalities (LMIs), which can be solved through convex optimization techniques. Due to considering bias terms in the system dynamic, the proposed approach can be regarded as the general case of the existing results. Furthermore, practical limitations on the amplitude of the input signal are considered and formulated in terms of LMIs. An electric vehicle dynamic with bias term is presented and hardware-in-the-loop (HiL) real-time and experiments are carried out to illustrate the effectiveness and merits of the proposed approach over the existing results.**

***Index Terms*— Nonlinear light-weighted electric vehicle, nonlinear model predictive control, linear parameter varying (LPV), linear matrix inequality (LMI), practical constraint.**

I. INTRODUCTION

IN recent years, because of global fuel supply, pollution issues and global warming, zero-polluting electric vehicles are a rapidly growing technology for energy management and environmental protection. The Light-Weighted Electric Vehicle (LWEV) has emerged as a promising alternative to improve fuel economy while meeting the tightened emission standards [1]–[4]. The LWEV is used in several applications including short-range transportations [5] A lot of work has been reported in the literature for reducing the energy and cost and increasing driving ranges in order to improve the performance of the energy management system [6]–[9]. Direct Current (DC) power is supplied by a battery and can provide larger startup torque. Consequently, a DC motor-based LWEV is known as a suitable choice and several DC motor-based EVs have been produced in the industry [10]. Furthermore, the DC motors have an effective operation as a braking device due to their fast torque response characteristics [11].

Several control approaches are presented for set-point stabilization and reference tracking of the speed control of nonlinear electric vehicle systems. In [12], a linear quadratic controller was presented for hybrid electric vehicles by controlling the throttle position. However, employing a linear controller for nonlinear systems reduces the performance of the closed-loop system. In [6], a probabilistic fuzzy neural network was proposed for a six-phase permanent magnet synchronous motor for LWEV. In [13], a fuzzy model-based controller was designed to control the speed of a permanent magnet synchronous motor and also experimentally tested. In [14], a fuzzy model-free controller was proposed for the wheel slip of electric vehicle's antilock braking systems. In [15], a new method based on stochastic drive cycles was developed for control optimization of an electric vehicle system. A robust adaptive sliding mode controller for uncertain hybrid electric vehicle systems was studied in [16]. Recently, a backstepping scheme was proposed for speed control of the electric vehicle systems [11]. Since the nonlinear dynamics of electric vehicles are not in the form of a strict feedback structure, a nonlinear mapping was first introduced. Then the backstepping controller was considered for reference trajectory issue of the electric vehicle speed. In [17], a feedback linearization method was proposed for the LWEV system. In this approach, the linear closed-loop system was stabilized by an LQR control scheme. In [18], an interior permanent magnet synchronous machine (IPMSM) based EV is controlled via an adaptive neural network method. It is assumed that the parameters of the IPMSM are unknown and an adaptive scheme is presented to assure the closed-loop stability and reference tracking through the Lyapunov stability theory. In [19], a terminal sliding mode control method is developed for the speed control of a hydrostatic heavy EV. The ramp angle is estimated by a disturbance observer and used in the controller design. However, in the above control methodologies, the practical limitations including the limited amplitude of the control input were not considered in the controller design procedure. Therefore, the performance of the mentioned controllers is decreased in the presence of practical constraints.

Besides the above-mentioned approaches in controlling the

N. Vafamand is with Department of Power and Control Engineering, School of Electrical and Computer Engineering, Shiraz University, Shiraz 71348-51154, Iran and Department of Energy Technology, Aalborg University, Aalborg East DK-9220, Denmark (E-mails: n.vafamand@shirazu.ac.ir and nav@et.aau.dk.

M.M. Arefi is Department of Power and Control Engineering, School of Electrical and Computer Engineering, Shiraz University, Shiraz 71348-51154, Iran (E-mail: arefi@shirazu.ac.ir).

M. H. Khooban, T. Dragičević and F. Blaabjerg are with Department of Energy Technology, Aalborg University, Aalborg East DK-9220, Denmark (E-mails: {kho, tdr, fbl}@et.aau.dk).

speed of EV systems, model predictive control technique (MPC) is an appropriate method, which effectively handles the constraints and addresses different challenging control problems such as disturbance rejection [20]–[23]. Based on the (Takagi-Sugeno) T-S or LPV models, nonlinear MPC (NMPC) is employed to DC microgrids [24], [25], active suspension systems [26], and chemical reactors [27], [28]. Recently in [29], [30], we proposed a nonlinear model predictive control for continuous-time T-S fuzzy systems based on a non-quadratic Lyapunov function and a non-parallel distributed compensation scheme and is applied to an EV system. However, considering the Lyapunov-based stability constraints can increase the computational burden of solving the online optimization problem and requires an analogous measurement of the system states. Furthermore, in most of the LPV-based MPC techniques in the literature, bias terms in the state space representation are not considered [26]–[33].

This paper develops a novel control strategy for the speed control of the constrained electric vehicle systems. A nonlinear model predictive control scheme under constraints is studied and formulated in terms of Linear Matrix Inequalities (LMIs). The proposed approach is based on an LPV model with bias terms. Firstly, the LPV model is used to exactly represent the nonlinear electric vehicle dynamics. Then, a model predictive scheme is proposed. The conditions associated with the model predictive controller design and the desired constraints are reformulated in terms of LMIs and solved by the numerical convex optimization approaches. Furthermore, controller design conditions are presented to force the system states to converge to their desired references on a finite horizon. Since the EVs comprise non-smooth functions originated by the friction forces; an exact polytopic LPV modeling of such systems is not possible. Therefore, the existing LPV-based MPC techniques lead to undesired closed-loop performance. The main advantage of our approach is that we consider a wider class of nonlinear state space LPV system and extend the existing results to this class of systems. This class of system can be used to exactly model non-smooth functions and, thereby, the proposed MPC method can be directly applied to the EV systems. To illustrate the advantages of the proposed approach over the recently published papers in the presence of practical constraints, the nonlinear model predictive, backstepping and feedback linearization controllers are applied to a nonlinear electric vehicle and the obtained experimental results are compared.

This paper is structured as follows: In Section 2, the nonlinear dynamics of the LWEV and its LPV model are proposed. In Section 3, the LMI formulations of the nonlinear predictive control problem are discussed. Experimental results are illustrated in Section 4. In the last section, the concluding remarks are given.

II. Light-Weighted Electric Vehicle System and ITS LPV Model

In this section, first, the description of the electric vehicle will be given in detail. Then, the equivalent LPV representation of the EV will be proposed.

A. *The Electric Vehicle Model*

Fig. 1 presents the schematic of an EV, which contains the balance among the rolling resistance F_{rr}, aerodynamic drag F_{ad}, hill climbing F_{hc}, and acceleration F_{ac} forces, exposed on a moving vehicle.

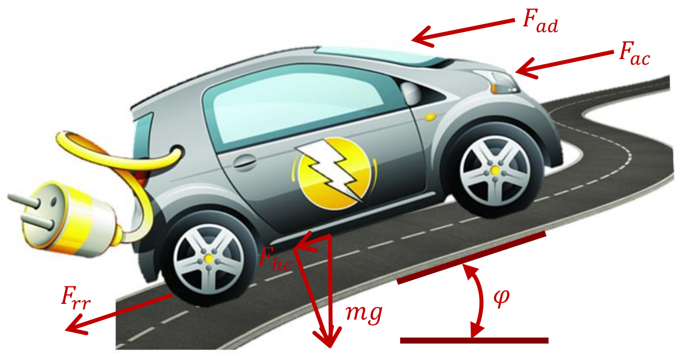


Fig. 1. The general scheme of light-weighted EV.

Take these factors into consideration, the total effective forces of vehicle dynamics, which control the kinetics of the wheels and vehicle can be considered as [29]:

$$F = \underbrace{\mu_{rr} mg\cos\varphi}_{\text{Rolling Resistance Force}} + \overbrace{{}^{1}/_{2}\, \rho A C_d v^2}^{\text{Aerodynamic Drag Force}} + \underbrace{mg\sin\varphi}_{\text{Hill Climbing Force}} + \overbrace{m\, {}^{dv}/_{dt}}^{\text{Acceleration Force}} \quad (1)$$

where μ_{rr} is the rolling resistance coefficient, m is the mass of the electric vehicle, g is the gravity acceleration, ρ is the air density, A is the frontal area of the vehicle, C_d is the drag coefficient, v is the driving velocity of the vehicle, and φ is the hill climbing angle. This resultant force F will create a counterproductive torque to the driving motor, which is illustrated by following formula [30],

$$T_L = F\left(\frac{r_e}{G}\right) \quad (2)$$

where r_e is the tyre radius of the electric vehicle, G the gearing ratio and the driving motor produced T_L the torque.

B. *Dynamics of the Electric Vehicle*

An EV system comprises the vehicle and motor dynamics. The DC motor is with serial connected armature and field windings and it is linked to the electric vehicle through the transmission part which includes the gearing system. Consequently, the actual speed of the electric vehicle is controlled by tuning the speed of the DC motor. The overall dynamic model of the EV system can be written as follows [11], [29]:

$$\begin{cases} \dfrac{d\omega}{dt} = \left(\dfrac{1}{J + m\left(\frac{r_e}{G}\right)^2}\right)\{L_{af} i^2 - B\omega - \left(\frac{r_e}{G}\right) \times \\ \left(\mu_{rr} mg\cos\varphi + {}^{1}/_{2}\, \rho A C_d \left(\frac{r_e}{G}\right)^2 \omega^2 + mg\sin\varphi\right)\} \\ \dfrac{di}{dt} = \left(\dfrac{1}{L_a + L_{field}}\right)\{u - (R_a + R_f)i - L_{af} i\omega\} \end{cases} \quad (3)$$

where ω is the motor angular speed and i is the armature current. Furthermore, L_a, R_a, L_{field} and R_f are the armature inductance, armature resistance, field winding inductance and field winding resistance, respectively. Also, B is the viscous coefficient, J is the inertia of the DC motor, u is the control input voltage, and L_{af} is the mutual inductance between the armature winding and the field winding [11].

C. *LPV Representation of the Electric Vehicle*

By exerting some simplifications on (3) and considering a small hill climbing angle to approximate $cos\varphi \cong 1$, one has

$$\begin{cases} \dot{x}_1 = \dfrac{K_1}{m+K_2}\{K_3x_2^2 - K_4x_1 - K_5x_1^2 - K_6m - K_7\sin\varphi\} \\ \dot{x}_2 = -K_8x_2 - K_9x_1x_2 + K_{10}u \\ y = x_1 \end{cases} \tag{4}$$

where $x = [x_1 \quad x_2\}^T = [\omega \quad i]^T$ is the state vector, y is the output. Also, $K_1 = \left(\frac{G}{r_e}\right)^2$, $K_2 = \left(\frac{G}{r_e}\right)^2 J$, $K_3 = L_{af}$, $K_4 = B$, $K_5 = 0.5\rho AC_d\left(\frac{r_e}{G}\right)^3$, $K_6 = \left(\frac{r_e}{G}\right)\mu_{rr}g$, $K_7 = \left(\frac{r_e}{G}\right)mg$, $K_8 = \frac{(R_a+R_f)}{(L_a+L_f)}$, $K_9 = \frac{L_{af}}{(L_a+L_f)}$, and $K_{10} = \frac{1}{(L_a+L_f)}$. The nonlinear dynamic equations (4) consist of three nonlinear terms (i.e. x_2^2, x_1^2 and x_1x_2). Since the states are bounded, they vary in the interval $x_i \in [-x_{i\min} \quad x_{i\max}]$ for $i = 1,2$. By defining the time varying parameters as

$$\begin{aligned} \theta_1 &= \left(\frac{x_{1max} - x_1}{x_{1max} - x_{1min}}\right)\left(\frac{x_{2max} - x_2}{x_{2max} - x_{2min}}\right); \\ \theta_2 &= \left(\frac{x_{1max} - x_1}{x_{1max} - x_{1min}}\right)\left(\frac{x_2 - x_{2min}}{x_{2max} - x_{2min}}\right); \\ \theta_3 &= \left(\frac{x_1 - x_{1min}}{x_{1max} - x_{1min}}\right)\left(\frac{x_{2max} - x_2}{x_{2max} - x_{2min}}\right); \\ \theta_4 &= \left(\frac{x_1 - x_{1min}}{x_{1max} - x_{1min}}\right)\left(\frac{x_2 - x_{2min}}{x_{2max} - x_{2min}}\right); \end{aligned} \tag{5}$$

the following LPV model of (4) is obtained:

$$\begin{cases} \dot{x} = \sum_{i=1}^{4}\theta_i\{A_ix + B_iu + E_i + D_iv\} \\ y = \sum_{i=1}^{4}\theta_iC_ix \end{cases} \tag{6}$$

where $x = [x_1 \ \ x_2]^T$, $v = sin\varphi$, and

$$A_1 = \begin{bmatrix} -\dfrac{K_1K_4 + K_1K_5z_{1min}}{m+K_2} & \dfrac{K_1K_3z_{2min}}{m+K_2} \\ -K_9z_{2min} & -K_8 \end{bmatrix};$$

$$A_2 = \begin{bmatrix} -\dfrac{K_1K_4 + K_1K_5z_{1min}}{m+K_2} & \dfrac{K_1K_3z_{2max}}{m+K_2} \\ -K_9z_{2max} & -K_8 \end{bmatrix};$$

$$A_3 = \begin{bmatrix} -\dfrac{K_1K_4 + K_1K_5z_{1max}}{m+K_2} & \dfrac{K_1K_3z_{2min}}{m+K_2} \\ -K_9z_{2min} & -K_8 \end{bmatrix};$$

$$A_4 = \begin{bmatrix} -\dfrac{K_1K_4 + K_1K_5z_{1max}}{m+K_2} & \dfrac{K_1K_3z_{2max}}{m+K_2} \\ -K_9z_{2max} & -K_8 \end{bmatrix};$$

$$B_1 = B_2 = B_3 = B_4 = \begin{bmatrix} 0 \\ K_{10} \end{bmatrix};$$

$$C_1 = C_2 = C_3 = C_4 = [1 \quad 0];$$

$$E_1 = E_2 = E_3 = E_4 = \begin{bmatrix} \dfrac{-K_1K_6m}{m+K_2} \\ 0 \end{bmatrix};$$

$$D_1 = D_2 = D_3 = D_4 = \begin{bmatrix} \dfrac{-K_1K_7}{m+K_2} \\ 0 \end{bmatrix}.$$

As it can be seen in (6), the nonlinear dynamics of the EV are modeled by a polytopic LPV model with 4 sub-systems, which are dynamically weighted by time varying parameters θ_i for $i = 1, \ldots, 4$. The time varying parameters are continuous and functions of the system states. Furthermore, the LPV representation is obtained for the region $\mathcal{R} \in \{x|\ x_i \in [-x_{i\min} \quad x_{i\max}]$ for $i = 1,2\}$. The lower and upper bounds can be selected based on the physical constraints of the EV. The DC motor of a practical EV can be supplied with a limited amplitude of the current and the overall EV has a limited velocity. Considering such constraints, the LPV system will be obtained. The sub-systems of (6) are linear and thereby, one can conclude that the polytopic LPV systems provide a nonlinear state-space representation, which is somehow affine with respect to the states.

III. THE LPV-BASED MODEL PREDICTIVE CONTROL SCHEME

MPC is a popular method, which utilizes a model to predict the future behavior of a system over a specific prediction horizon [34]–[36]. At each time step, an online optimization problem is solved to obtain the control signal. The online calculation can be carried out by a quadratic optimization or the LMI numerical techniques, which are powerful tools for solving the control problems that do not have analytical solutions [37]–[39]. The main theoretical results of the MPC related to the stability come from a state space formulation, which can easily be extended to nonlinear processes [40]. Nonlinear MPC techniques can be formulated in terms of LMIs by considering the T-S or LPV modeling [27], [41]. In this section, a nonlinear model predictive controller based on the LPV model will be studied. Consider the following discrete-time LPV system with bias term:

$$\begin{cases} x(t+1) = \sum_{i=1}^{r}\theta_iA_ix(t) + \sum_{i=1}^{r}\theta_iB_iu(t) + \sum_{i=1}^{r}\theta_iE_i \\ \qquad\quad = A_\theta x(t) + B_\theta u(t) + E_\theta \\ y(t) = \sum_{i=1}^{r}\theta_iC_ix(t) = C_\theta x(t) \end{cases} \tag{7}$$

where E_θ is the bias term and the following cost function [40]:

$$\begin{aligned} J(N_p, N_u) = \sum_{j=1}^{N_p}\delta(j)[\hat{y}(t+j|t) - w(t+j)]^2 \\ + \sum_{j=1}^{N_u}\lambda(j)[u(t+j-1)]^2 \end{aligned} \tag{8}$$

where N_p and N_u are the prediction and control horizons, respectively, and $\hat{y}(t+j|t)$ is the optimal j-step ahead prediction of the output and $w(t+j)$ is the function of future reference. The coefficients $\delta(j)$ and $\lambda(j)$ determine the weights of the tracking error and the energy effort terms in the cost function (8), respectively. Generally, there is a tradeoff between the tracking error and the energy of the control input. If high values of $\delta(j)$ for $j = 1, \ldots, N_p$ are selected, minimizing the tracking error will be primitive. Thereby, the controller is designed so that it better minimizes the tracking error. On the other hand, if the coefficient $\lambda(j)$ is chosen large, then the impact of the term control input energy in the optimization is enlarged. Therefore, the controller is designed so that it better minimizes the tracking error.

In order to obtain the control inputs $u(t+j-1)$, it is necessary to minimize the cost function J given in (8). To do this, the values of the predicted outputs $\hat{y}(t+j|t)$ are calculated as a function of the past values of the system characteristics and future control signals by using the LPV model (7) substituted in the cost function. The predictions are calculated as

$$Y = \begin{bmatrix} C_\theta A_\theta \\ C_\theta A_\theta^2 \\ \vdots \\ C_\theta A_\theta^{N_p} \end{bmatrix} x(t) + \begin{bmatrix} C_\theta E_\theta \\ C_\theta (I + A_\theta) E_\theta \\ \vdots \\ \sum_{i=0}^{N_p-1} C_\theta A_\theta^i E_\theta \end{bmatrix} + \begin{bmatrix} C_\theta B_\theta & \ldots & 0 \\ C_\theta (A_\theta) B_\theta & \ldots & 0 \\ \vdots & \ddots & \vdots \\ C_\theta A_\theta^{N_p-1} B_\theta & \ldots & C_\theta B_\theta \end{bmatrix} U \tag{9}$$

where $Y = \left[\hat{y}(t+1|t)\ \hat{y}(t+2|t)\ \ldots\ \hat{y}\left(t+N_p|t\right)\right]^T$ and $U = [u(t)\ u(t+1) \ldots\ u(t+N_u-1)]^T$. Equation (9) can be expressed in a vector form as

$$Y = \Psi + \Theta U \tag{10}$$

where

$$\Psi = \begin{bmatrix} C_\theta A_\theta \\ C_\theta A_\theta^2 \\ \vdots \\ C_\theta A_\theta^{N_p} \end{bmatrix} x(t) + \begin{bmatrix} C_\theta E_\theta \\ C_\theta (I + A_\theta) E_\theta \\ \vdots \\ \sum_{i=0}^{N_p-1} C_\theta A_\theta^i E_\theta \end{bmatrix};$$

$$\Theta = \begin{bmatrix} C_\theta B_\theta & \ldots & 0 \\ C_\theta (A_\theta) B_\theta & \ldots & 0 \\ \vdots & \ddots & \vdots \\ C_\theta A_\theta^{N_p-1} B_\theta & \ldots & C_\theta B_\theta \end{bmatrix}.$$

Rewriting the cost function (8) in a vector representation, yields

$$J(N_p, N_u) = (Y - W)^T \Delta (Y - W) + U^T \Lambda U \tag{11}$$

where $W = \left[w(t+1)\ \ w(t+2)\ \ldots\ w\left(t+N_p\right)\right]^T$, $\Delta = \mathrm{diag}\{\delta(1), \delta(2), \ldots \delta(N_p)\}$ and $\Lambda = \mathrm{diag}\{\lambda(1), \lambda(2), \ldots, \lambda(N_p)\}$ with $\mathrm{diag}\{.\}$ stands for a diagonal matrix. By substituting (10) into (11), one has

$$J(N_p, N_u) = U^T H U + K U + U^T K^T + G \tag{12}$$

where

$$H = \Theta^T \Delta \Theta + \Lambda > 0; \quad \mathrm{K} = (\Psi - W)^T \Delta \Theta;$$
$$\mathrm{G} = (\Psi - \mathrm{W})^T \Delta (\Psi - W).$$

The optimization problem is now to minimize J with respect to U, subject to constraints. To address this issue, an upper bound J^* is introduced and minimized through the convex optimization approaches.

$$J(N_p, N_u) = U^T H U + K U + U^T K^T + G < J^* \tag{13}$$

Applying the Schur complement [42] on (13) results in:

$$\begin{bmatrix} J^* - G - K^T U + U^T K^T & U^T \\ U & H^{-1} \end{bmatrix} > 0 \tag{14}$$

In the following, the constraints on the saturated control input will be derived in terms of LMIs. Consider the following constraint on the amplitude of the control signal:

$$\xi_{\min}(t+j-1) < u(t+j-1) < \xi_{\max}(t+j-1) \quad \text{for} \quad j = 1, \ldots, N_u + 1. \tag{15}$$

The constraint (15) can be formulated as follows:

$$\Xi_{\min} < IU < \Xi_{\max} \tag{16}$$

or equivalently

$$\begin{bmatrix} I \\ -I \end{bmatrix} U < \begin{bmatrix} \Xi_{max} \\ -\Xi_{\min} \end{bmatrix} \tag{17}$$

where $\Xi_{\max} = [\xi_{\max}(t), \ldots, \xi_{\max}(t+N_u)]^T$, $\Xi_{\min} = [\xi_{\min}(t), \ldots, \xi_{\min}(t+N_u)]^T$ and I is the identity matrix with appropriate dimensions.

Remark 1 (advantages of the proposed approach): By comparing the proposed MPC-based method with other nonlinear control methods, one can conclude that:

1. The proposed approach is more robust against the system uncertainty which is evident from the simulation results. The reason is that the future behavior of the plant is also considered in the controller design; and at each step, an online optimization is performed to design the optimal value of the control input.
2. The proposed approach can effectively handle input constraints such as actuator saturation. However, the other conventional methods lead to conservative results. Because, the proposed approach deploys the online numerical techniques and at each instant, the constraints are well-considered in the controller design.

These merits are some of the main advantages of the model predictive controller over the conventional controllers including the backstepping [11], sliding mode [16], and feedback linearization [17] methods. Additionally, in recent years some predictive controllers are presented for the EV case study [29], [30]. In [29] and [30], an infinite prediction horizon scheme is considered and at each step, the gains of a nonlinear state feedback controller are computed. These approaches have three main drawbacks:

I) Considering an infinite prediction horizon increases the computational burden of the online calculations.

II) The structure of the presented controllers (i.e. state feedback) is complex and it needs an analogous measurement of the EV's states.

III) The approaches [29] and [30] are applicable to those systems with smooth nonlinear terms and infinite norm-2 disturbance inputs. However, the mechanical part of an EV comprises frictions, which are smooth and modeled by signum functions. Also, a hill climbing angle, which is mainly considered as disturbance is better described by an infinite norm-∞ specification. Therefore, one needs to approximate the non-smooth functions by the smooth ones to deploy [29], [30]. Furthermore, both approaches [29], [30] consider the hill climbing angles as zero (same as [11] and [17]) to design their controllers.

However, the proposed approach handles these difficulties by considering a finite prediction horizon and a simpler structure of the controller. The proposed controller is not a state feedback one and each step, the optimal value of the control input is directly designed. Moreover, by considering a nonlinear bias term in the system dynamic (i.e. $\sum_{i=1}^{r}\theta_i E_i$ in (7)), a novel predictive controller is proposed, which is explicitly applicable for non-smooth functions and amplitude bounded disturbances; and thereby the proposed approach is more suitable than the existing state-of-the-art MPCs for the EV case studies.

IV. Experimental Results

In this section, the proposed controller is applied to the nonlinear electric vehicle. To evaluate the efficiency of the proposed nonlinear model predictive controller, the obtained results are compared with the backstepping controller [11], feedback linearization [17], and TS-MPC [43] which are the latest researches in the present problem.

Four cases are considered. In the first case, the hill climbing angle is set to zero and the tracking performances of the mentioned control laws are investigated. In the second case, for a constant speed reference, the hill climbing angle changes and the robustness of the controllers against the external disturbance are studied. In the third case, the system uncertainty is considered and the closed-loop performance in the presence of the uncertainty is studied. In these three cases, the hardware-in-the-loop (HIL) simulation approach is utilized to evaluate the results. The HiL setup is illustrated in Fig. 2 and it is consisting of: I) OPAL-RT as a real-time simulator (RTS), II) a PC as the command station (programming host) in which the Matlab/Simulink based code executed on the OPAL-RT is generated, and III) a router used as a connector of all the setup devices in the same sub-network. The OPAL-RT is also connected to the DK60 board through Ethernet port [29]. Finally, in the last case, the experimental test on a practical DC motor is carried out. The parameters of the EV system utilized in this study are shown in Table I.

Fig. 2. The real-time setup for testing the proposed method.

TABLE I. EV system parameters

Symbol	Value	Symbol	Value
$R_a + R_f$	$0.2\ [\Omega]$	u	$0\sim60\ [V]$
$L_a + L_f$	$6.008\ [mH]$	I	$0\sim5\ [A]$
r	$0.25\ [m]$	ω	$0\sim50\ [Km/hr]$
J	$0.05\ [Kg.m^2]$	m	$800\ [Kg]$
L_{af}	$1.776\ [mH]$	A	$1.8\ [m^2]$
μ_{rr}	0.015	G	11
B	$0.0002\ [m^2/s]$	C_d	0.3
ρ	$1.225\ [Kg/m3]$		

Case 1: In this case, the hill climbing angle is assumed to be zero and the electric vehicle moves on a horizontal path. The ranges of the EV states, for which the LPV model (6) is obtained, are $0 \le \omega \le 50\ [Km/hr]$ and $0 \le I \le 5\ [A]$. The nonlinear model predictive controller is constructed based on the discretized LPV model of (6) with the period $T_s = 1\ sec$ and the prediction and control horizons $N_p = N_u = 3$. Also, the weighting functions are selected as $\delta(j) = 1$ and $\lambda(j) = 0.01$. Furthermore, the lower and upper bounds of the saturated input constraint are set as $u_{\min} = 0$ and $u_{\max} = 60$.

The tuning parameter of the backstepping control law given in [11] is selected such that the obtained control signal effort does not experience a saturation situation. Therefore, this tuning parameter is chosen as $\bar{k}_2 = 0.1$.

It should be noted that the nonlinear model and its LPV representation is assumed to be controllable. If x_1 is not controllable, then Θ given in (10) will be zero, and the control input calculated from the NMPC optimization problem will be zero. The same assumption of controllability for the other nonlinear control schemes must be held too.

The LWEV system (6) is controllable, if $x_2 \neq 0$. Therefore, for simulation, the initial condition is chosen as $x(0) = [0,1]^T$. Fig. 3 shows the state evolutions and control effort of the closed-loop electric vehicle system for the proposed NMPC controller and the recently presented nonlinear controllers in hand.

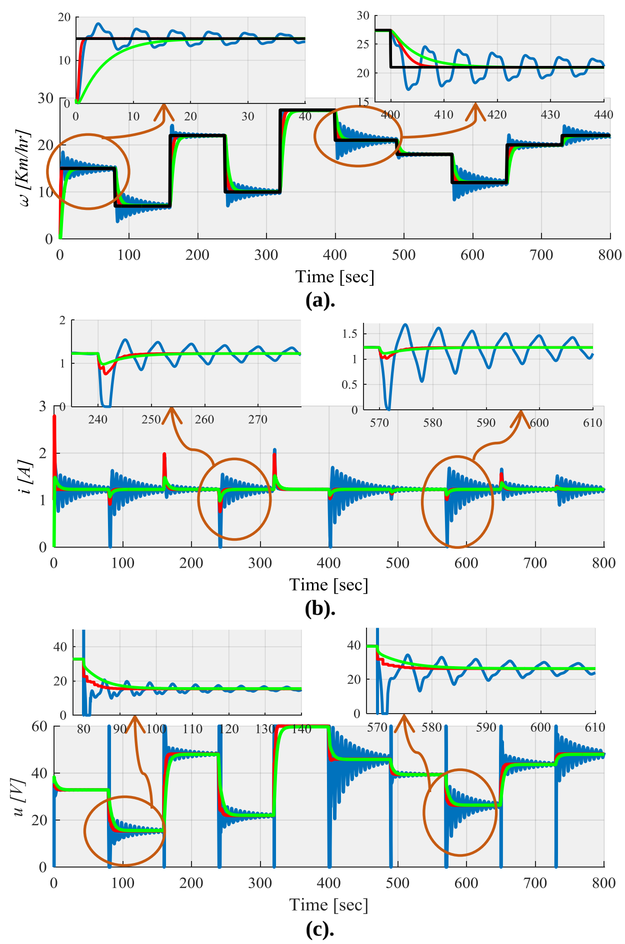


Fig. 3. Case 1 (feedback linearization by "green", proposed approach by "red", backstepping by "blue" and reference by "black"): **(a).** the motor angular speed, **(b).** the armature current, **(c).** the input voltage.

As can be seen in Fig. 3, the proposed NMPC has a better transient performance than the feedback linearization [17] and the backstepping [11] approaches for speed control of the LWEV system. The closed-loop LWEV system output converges to the desired reference, without any oscillation behavior.

Case 2: In this case, the effect of the hill climbing angle φ is investigated on the closed-loop system. Therefore, the reference and the angle are set as $\omega_d = 18\ km/hr$ and

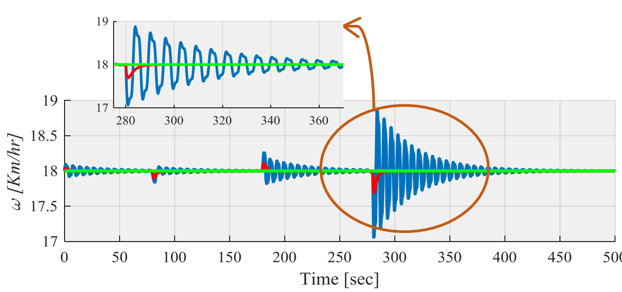
$$\varphi = \begin{cases} 0 & \text{for} \quad 0 < t < 80 \\ 3 & \text{for} \quad 80 < t < 180 \\ 0 & \text{for} \quad 180 < t < 280 \\ 10 & \text{for} \quad 280 < t < 500 \end{cases} \tag{18}$$

The simulation is performed by selecting the initial value of the electric vehicle $x(0) = [18, 1.24]^T$. The initial conditions are chosen such that the electric vehicle roughly is in its steady state phase. Fig. 4 shows the state evolutions and control effort of the closed-loop electric vehicle system for different approaches. Fig. 4 illustrates that the proposed NMPC can effectively alleviate the effect of the hill climbing angle variation on the speed of the LWEV and maintains the LWEV speed at its desired reference. From Fig. 4 one can conclude that the changes and oscillations in the closed-loop LWEV output derived based on the NMPC are much less than those of the backstepping approach [11]. In addition, the feedback linearization technique [17] fails to stabilize the EV's speed, because such a method is not robust against system uncertainties and parameter variations.

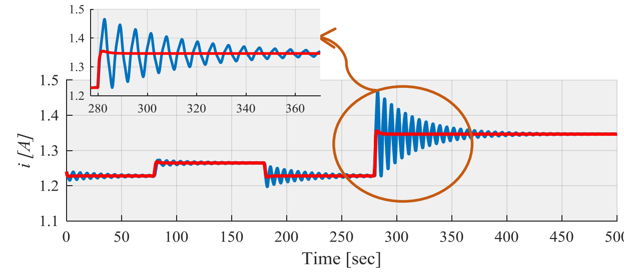
Case 3: In order to show the robustness of the proposed controller against the changes in system parameters, some variations are made in some of the system parameters given in Table I. The changes in the percentage of the system parameters are shown in Table II.

TABLE II. Uncertainty analysis using the parameters of Electric Vehicle

Parameters	Variation Range
$\Delta R = R_a + R_f\ (\Omega)$	+10%
$\Delta L = L_a + L_f\ (mH)$	-5%
$r_e\ (m)$	+10%
$J\ (Kg\ m^2)$	-25%
$m\ (Kg)$	+25%
C_d	-10%
μ_{rr}	+20%
$\rho\ (Kg/m)$	+15%



(a).



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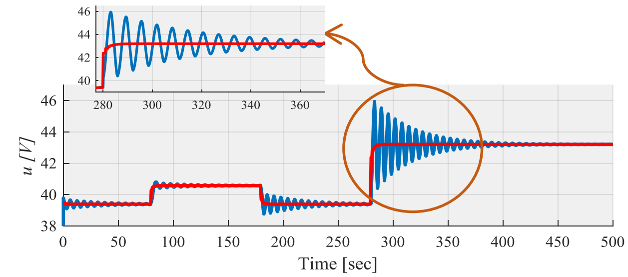

(c).

Fig. 4. Case 2 (proposed approach by "red", backstepping by "blue" and reference by "green"): **(a).** the motor angular speed, **(b).** the armature current, **(c).** the input voltage.

For the simulations, all initial values and controller parameters are set as in Case 1. The proposed controller is still designed based on the nominal parameters of the system given in Table I. Therefore, the system parameter variations do not affect the design procedure of the proposed control law and only may degrade the closed-loop tracking performance since the actual EV model differs from the nominal one used in the controller. In addition, the TS-MPC approach [29] is considered. Fig. 5 illustrates the closed-loop system state evolution and control input signal. As it is evident from Fig. 5, the feedback linearization approach cannot exactly track the desired reference in the presence of the uncertainty; and the EV speed has a bias compared to the reference. Consequently, a different level of the input current (about 2 A) is injected when the feedback linearization method is employed. Also, the backstepping approach experiences a high chattering phenomenon. Furthermore, by promptly changing the set point, the TS-MPC controller leads to transient overshoot oscillations. This is due to the fact that the approximating the non-smooth functions in deriving the Takagi-Sugeno (TS) model [43]. The best performance belongs to the proposed MPC controller.

Case 4 (Experimental Implementation Using TMS320F28335 Digital Signal Processor (DSP)): In this case, the experimental examination of the proposed LPV-based MPC is conducted. By using a high-performance TMS320F28335 DSP, the experimental results of the speed control of a nonlinear DC motor are carried out. The interested readers can refer to [30] for further implementation details. In addition, the New European Driving Cycle (NEDC) is considered to examine the performance of the proposed controller.

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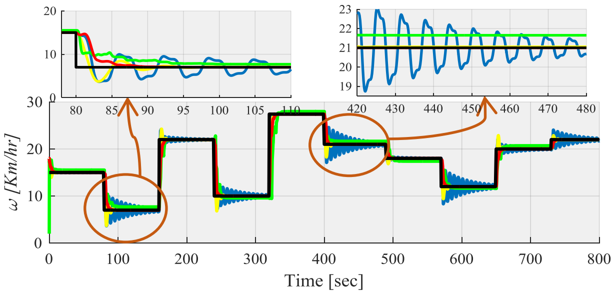
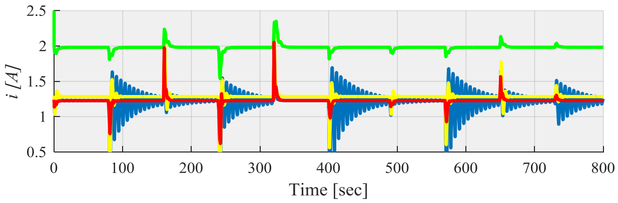


(a).



(b).

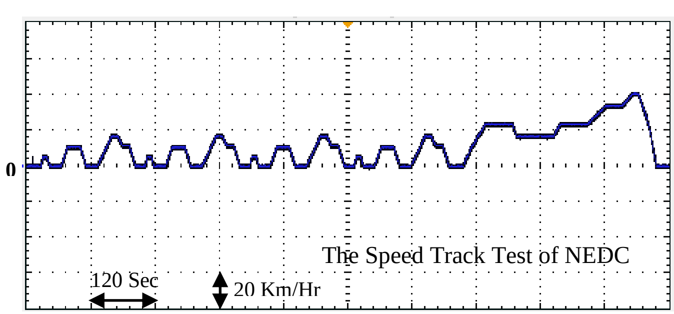
Fig. 5. Case 3 (feedback linearization by "green", proposed approach by "red", backstepping by "blue", TS-MPC by "yellow", and reference by "black"): **(a).** the motor angular speed, **(b).** the armature current.

Fig. 6 shows the experimental NEDC speed test, the control input, and the motor angular speed error. As demonstrated in Fig. 6, the EV system with the proposed controller can track the desired reference with an error of the order 10^{-1}. Besides, Fig. 6(b) depicts that the control signal of the suggested novel approach is limited (48 Volt). This is very important because the batteries in the EVs are limited.

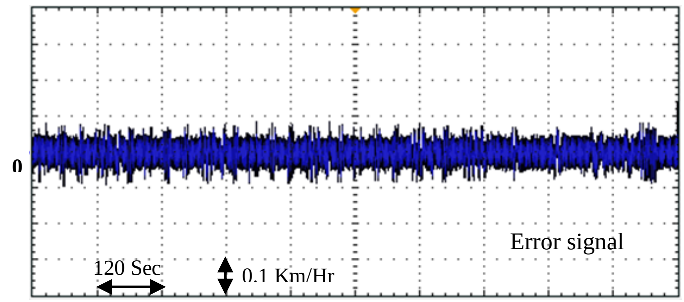
In addition, the normalized integral of the square error (NISE) (i.e. $\int_0^t \left(\frac{e(\tau)}{\omega(\tau)}\right)^2 d\tau$), the normalized integral of absolute error (NIAE) (i.e. $\int_0^t \left|\frac{e(\tau)}{\omega(\tau)}\right| d\tau$), and the power of the control input signal (i.e. $\frac{1}{t}\int_0^t \big(u(\tau)\big)^2 d\tau$) for the interval $t \in [0{,}1200]$ seconds are provided in Table III. To sum up, it is shown that the real-time simulation results based OPAL-RT technology and experimental results based TMS320F28335 DSP are very similar to each other for the evaluations of the proposed control approach.

TABLE III. Closed-loop performance of the experimental test

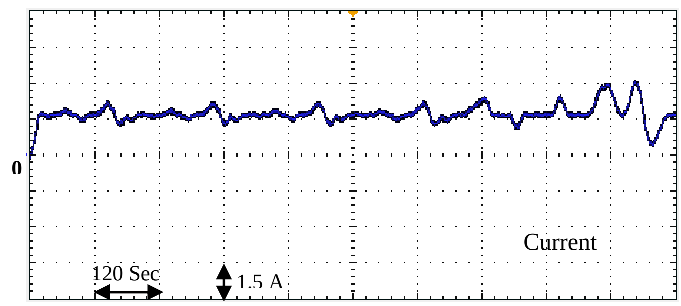
Performance	Value
NISE	0.0132
NIAE	0.512
Control input power	247.154



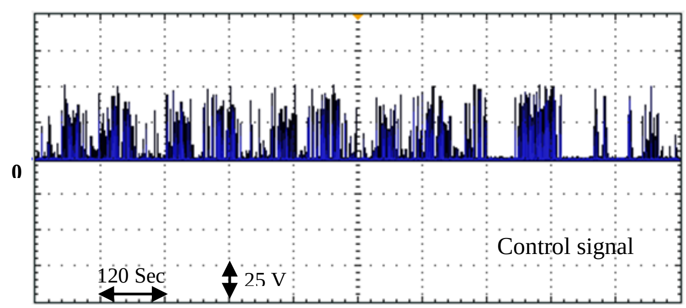
(a).



(b).



(c).



(d).

Fig. 6. Case 4 (Experimental results of the proposed controller for NEDC reference speed command) **(a).** the NEDC reference, **(b).** the error of the EV speed from the desired reference. **(c).** the DC motor current **(d).** the control input signal.

V. Conclusion

In this paper, a nonlinear model predictive control (NMPC) method was proposed for the speed control of constrained nonlinear light-weighted electric vehicles (LWEVs). The basis of the NMPC was a linear parameter varying (LPV) model, which facilitates formulating the controller design conditions in terms of linear matrix inequalities and generalized Eigenvalue problem (GEVP). Therefore, at each time step of the NMPC controller, the input signal can be obtained through the convex optimization techniques. Also, practical limitations on the amplitude of the input signal were considered and formulated in terms of LMIs. Experimental results have illustrated that the proposed approach has a fast convergence of the closed-loop LWEV system output without any oscillations. In addition, the NMPC was robust to the hill climbing angle. Therefore, the variation in the hill climbing angle has a small destructive effect on the speed of the LWEV. For the future work, considering the optimal section of the coefficients of the cost function is an important research area. Also, considering the motor power and torque constraints and other types of motors such as permanent magnet DC can be of great importance.

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Navid Vafamand was born in Iran in 1990. He received his B.Sc. degree in electrical engineering and M.Sc. degree in control engineering form Shiraz University of Technology, Iran, in 2012 and 2014, respectively. He is a Ph. D. candidate in control engineering in Shiraz University, Iran. Currently, he is a Ph.D. visiting student at Aalborg University, Denmark.

His main research interests include Takagi-Sugeno (TS) fuzzy models, linear parameter varying (LPV) systems, linear matrix inequality (LMI), predictive control, and stability and control of power systems.

Mr. Vafamand has published more than 50 publications on journals and conferences, plus one book chapter.

Mohammad Mehdi Arefi (M'17–SM'17) was born in 1982. He received the B.Sc. degree from the Department of Electrical Engineering, Shiraz University, Shiraz, Iran, in 2004, and the M.Sc. and Ph.D. degrees from the Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran, in 2007 and 2011, respectively. He is an Associate Professor with the Department of Power and Control Engineering, School of Electrical and Computer Engineering, Shiraz University. His current research interests include adaptive robust control, nonlinear and chaos control, application of neural network in nonlinear control, observer-based control, and model predictive control. Dr. Arefi is in the editorial board of some journals, including the Iranian Journal of Science and Technology, Transactions of Electrical Engineering, and Industrial Control Magazine.

Mohammad-Hassan Khooban (M'13-SM'18) was born in Shiraz, Iran, in 1988. He received the Ph.D. degree from Shiraz University of Technology, Shiraz, Iran, in 2017. He was a research assistant with the University of Aalborg, Aalborg, Denmark from 2016 to 2017 conducting research on Microgrids and Marine Power Systems. Currently, he is a PostDoctoral Associate at Aalborg University, Denmark.

His research interests include control theory and application, power electronics and its applications in power systems, industrial electronics, and renewable energy systems.

Dr. Khooban is author or co-author of more than 100 publications on journals and international conferences, plus one book chapter and one patent. He is currently serving as an Associate Editor of the Complexity Journal and IEEE TRANSACTIONS ON ENERGY CONVERSION.

Tomislav Dragičević (S'09-M'13-SM'17) received the M.Sc. and the industrial Ph.D. degrees in Electrical Engineering from the Faculty of Electrical Engineering, Zagreb, Croatia, in 2009 and 2013, respectively. From 2013 until 2016 he has been a Postdoctoral research associate at Aalborg University, Denmark. From March 2016 he is an Associate Professor at Aalborg University, Denmark. He made a guest professor stay at Nottingham University, UK during spring/summer of 2018.

His principal field of interest is overall system design of autonomous and grid connected DC and AC microgrids, and application of advanced modeling and control concepts to power electronic systems.

Dr. Tomislav has authored and co-authored more than 140 technical papers (more than 55 of them are published in international journals, mostly IEEE Transactions) in his domain of interest and 8 book chapters and a book in the field.

He serves as an Associate Editor in the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS and in the Journal of Power Electronics. Dr. Dragičević is a recipient of a Končar prize for the best industrial PhD thesis in Croatia, and a Robert Mayer Energy Conservation award.

Frede Blaabjerg (S'86–M'88–SM'97–F'03) was with ABB-Scandia, Randers, Denmark, from 1987 to 1988. From 1988 to 1992, he got the PhD degree in Electrical Engineering at Aalborg University in 1995. He became an Assistant Professor in 1992, an Associate Professor in 1996, and a Full Professor of power electronics and drives in 1998. From 2017 he became a Villum Investigator. He is honoris causa at University Politehnica Timisoara (UPT), Romania and Tallinn Technical University (TTU) in Estonia.

His current research interests include power electronics and its applications such as in wind turbines, PV systems, reliability, harmonics and adjustable speed drives. He has published more than 600 journal papers in the fields of power electronics and its applications. He is the co-author of four monographs and editor of ten books in power electronics and its applications.

Prof. Blaabjerg has received 28 IEEE Prize Paper Awards, the IEEE PELS Distinguished Service Award in 2009, the EPE-PEMC Council Award in 2010, the IEEE William E. Newell Power Electronics Award 2014 and the Villum Kann Rasmussen Research Award 2014. He was the Editor-in-Chief of the IEEE TRANSACTIONS ON POWER ELECTRONICS from 2006 to 2012. He has been Distinguished Lecturer for the IEEE Power Electronics Society from 2005 to 2007 and for the IEEE Industry Applications Society from 2010 to 2011 as well as 2017 to 2018. In 2018 he is President Elect of IEEE Power Electronics Society. He serves as Vice-President of the Danish Academy of Technical Sciences. He is nominated in 2014, 2015, 2016 and 2017 by Thomson Reuters to be between the most 250 cited researchers in Engineering in the world.